Declaration of [redacted] Ph.D

November 30, 2020

Pursuant to 28 U.S.C Section 1746, I, [redacted], make the following declaration.

1. I am over the age of 21 years and I am under no legal disability, which would prevent me from giving this declaration.

2. [redacted] has a Ph.D in Electrical Engineering from the University of California at Davis and a Masters degree in Mathematics from the University of California at Berkeley. I have been employed, for over 28 years, in the signal processing and wireless signal processing domain, with an emphasis on statistical signal processing. I have published numerous journal and conference articles. Additionally, I have held Top Secret and SAP clearances and I am an inventor of nearly 30 patents, one of which has over 1000 citations in the field of MIMO communications (Multiple Input Multiple Output).

3. I reside at [redacted], [redacted].

4. Given the data sources referenced in this document, I assert that in Georgia, Pennsylvania and the city of Milwaukee, a simple statistical model of vote fraud is a better fit to the sudden jump in Biden vote percentages among absentee ballots received later in the counting process of the 2020 presidential election. It is also a better fit when constrained to a single large Metropolitan area such as Milwaukee..

5. Given the same data sources, I also assert that Milwaukee precincts exhibit statistical anomalies that are not normally present in fair elections.. The fraud model hypothesis in Milwaukee has a posterior probability of 100% to machine precision. This model predicts 105,639 fraudulent Biden ballots in Milwaukee.

6. I assert that the data suggests aberrant statistical anomalies in the vote counts in Michigan, when observed as a function of time.

Signature:

Supporting evidence for the assertions in (4) and 5 is provided in the following pages.

1 Impact of Fraud on the Election

In the analysis that follows, it is possible to obtain rough estimates on how vote fraud could possibly have effected the election. In Georgia, there is evidence that votes were actually switched from Trump to Biden. As many as 51,110 Biden votes were fraudulent and as many as 51,110 votes could be added to Trump. An audit to determine vote switching will be more difficult, since it is likely the Trump ballots have been destroyed in Georgia, based on reports of ballots being shredded there. If instead we presume that Bidens fraudulent votes were simply added to the totals, then we estimate that 104,107 ballots should be removed from Biden's totals.

In Pennsylvania, from just one batch of absentee ballots, approximately 72668 of them are estimated to be fraudulent Biden votes. Our analysis of Milwaukee shows that 105,639 Biden ballots could be fraudulent. Moreover there is evidence of vote switching here, which might give as many as 42365 additional ballots to Trump, and remove the same from Biden.

Michigan yields an estimate of 237,140 fraudulent Biden votes added to the total, using conservative estimates of the Biden percentage among the new ballots.

2 Statistical Model

The simplest statistical model for computing the probabilities for an election outcome is a binomial distribution, which assigns a probability p for a given person within the population to select a candidate. If we assume that each person chooses their candidate independently, then we obtain the Binomial distribution in the form,

$$P(k|N) \equiv {}_N C_k p^k \left(1-p\right)^{N-k}, \tag{1}$$

where $P(k|N)$ is the probability that you observe k votes for a candidate in a population of N voters, and where ${}_N C_k$ is the number of ways to choose k people out of a group of N people.

For larger N, the binomial distribution can be approximated by a Gaussian distribution, which is used in the election fraud analysis in [1]. The chief reason for this is the difficulty of computing $P(k|N)$ for large N and k. However this problem can be overcome by computing the probabilities in the log domain and using the log beta function to compute ${}_N C_k$.

For this analysis it is more useful to compute the probabilities as a function of f the observed fraction of the candidate's votes. In this formulation we have $k = Nf$, and $N - k = N\left(1-f\right)$, and therefore we define the fractional probability as,

$$B_N(f) \equiv {}_N C_{Nf}\, p^{Nf} \left(1-p\right)^{N(1-f)}. \tag{2}$$

2.1 Fraud Model

To model voting fraud we assume a fixed fraction α of votes are given to the cheater. The pool of available voters who actually voted is now $N(1-\alpha)$. The fraction who actually voted for the cheater is given by $f-\alpha$. The probability that the fraction f voters reported for the cheater, with the fraction α stolen, can therefore be written as,

$$C_{N,\alpha}(f) \equiv B_{N(1-\alpha)}(f-\alpha). \tag{3}$$

This is similar to the fraud model used in the election fraud analysis given in [1]. We use the Binomial distribution directly, rather than the Gaussian distribution, since it should be more accurate for small N, k or f.

2.2 Posterior Probability of Fraud Model

A hypothesis test can now be set up between the standard voting statistics of (2) vs the statistics of the fraud model (3). If we use Bayesian inference we can compute an estimate of the posterior probability of the fraud model. This can be written as,

$$P(F|f) = \frac{C_{N,\alpha}(f)p_F}{C_{N,\alpha}(f)p_F + B_N(f)(1-p_F)},$$

where p_F is the prior probability of fraud. In our investigation we assume fraud is unlikely and set $p_F = 0.01$.

3 Analysis of Absentee Ballots in the 2020 Election

For this analysis we extracted data from the all_states_timeseries.csv file, which can be found at the internet url: https://wiki.audittheelection.com/index.php/Datasets. We look at the absentee ballot results near the beginning of the time series and then compare it to the end or the middle of the period, after a sufficient enough ballots were added.

For the models in Section 2 we assign the probability p of a Biden vote using the final data. This assumption is actually more favorable to the cheater. As mentioned earlier we set the prior probability of fraud to $p_F = 0.01$, and the cheating fraction, α, is set to $\alpha = f - p$, where f is the observed Biden fraction in the newly added ballots. This isolates the statistics of the added ballots from the final observed statistics.

We focus on the absentee ballots, because they are dominated by large democratic cities and there is no obvious reason why those statistics should change appreciably over time. Furthermore it should be noted that the start time for this data, mid day Nov. 4., was well after some of the larger absentee ballot dumps occured.

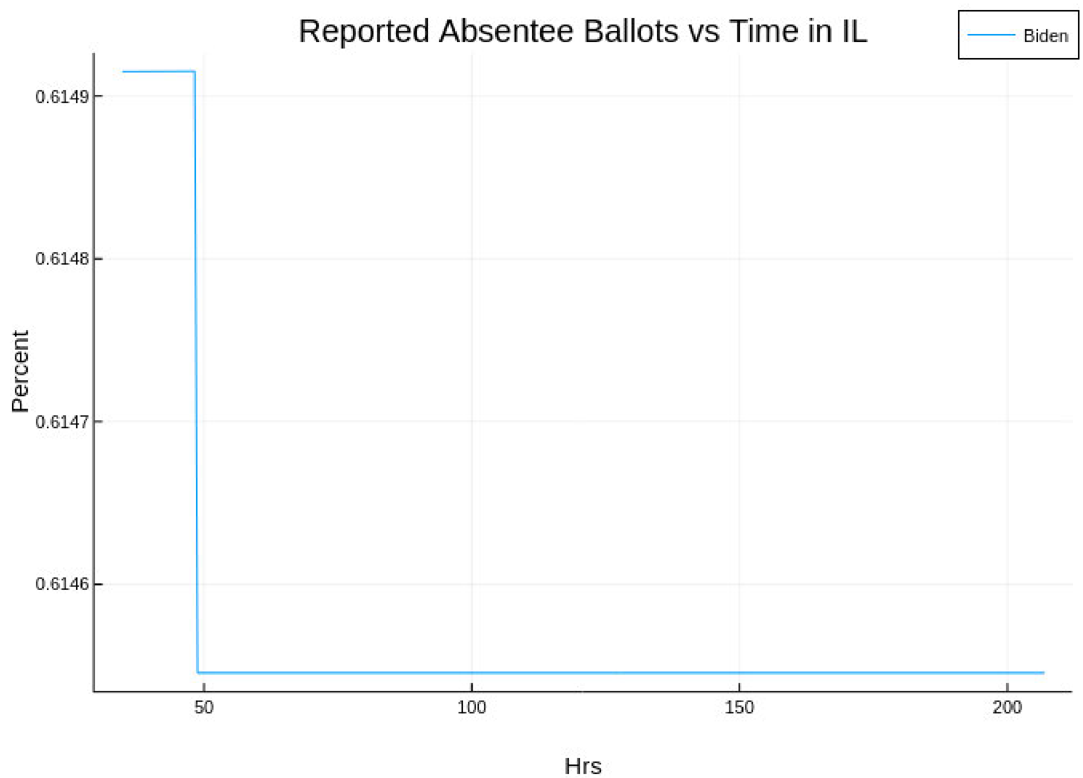

Figure 1: Reported Biden Fraction In Illinois vs Time

3.1 Control Case Illinois

We choose Illinois as a control case, since it has a significant number of absentee ballots that were counted later and provides a fairly clean baseline. The reported Biden fraction vs time is given in Figure 1.

As we can see there is not much change in the Biden statistics from the initial 601,714 absentee ballots when compared with the 54,117 ballots that were added. This is further shown by the bar chart in Figure 2.

Using our formula for the posterior probability of fraud in (3) we obtain the probability that the fraud model is correct of 6.5%. This lends good support to the idea that the Illinois absentee ballots were counted fairly.

3.2 Analysis of Georgia Absentee Ballots

The Georgia absentee ballot count started at 3,701,005 and 303,988 ballots were added. The Biden fraction among absentee ballots as a function of time is shown in Figure (3). This plot shows a statistical abnormality in that the

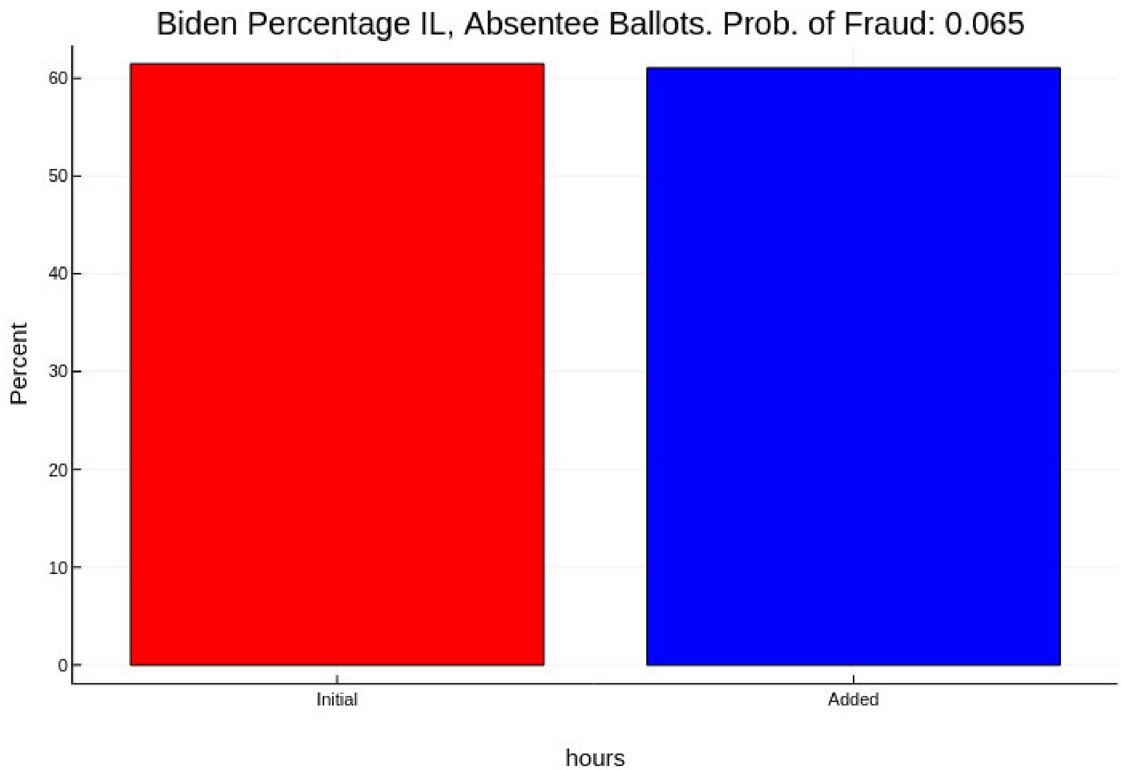

Figure 2: Before and Added Biden Fraction

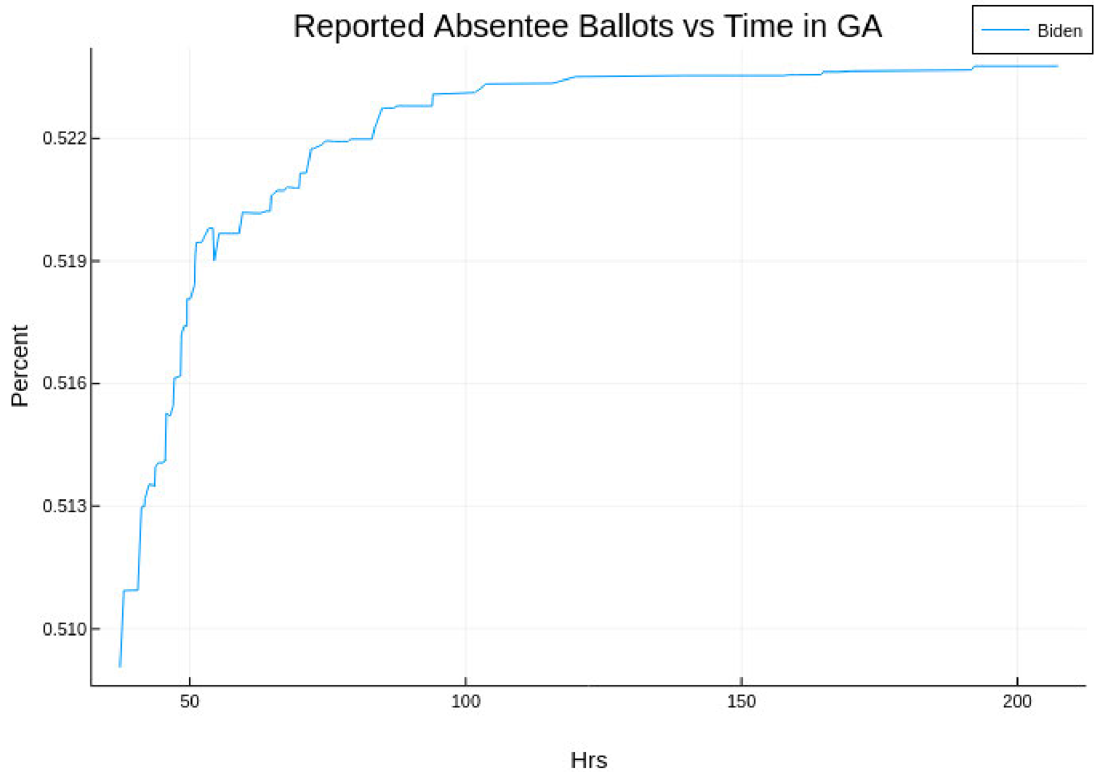

Figure 3: Georgia Absentee Ballots vs Time: (Biden Fraction)

Biden fraction appears to always be increasing. This is statistically unlikely and is not typically seen in fair elections. Normally you would see a mixture of votes of Biden and his opponents, and would see random deviation around the asymptote.

We investigate this phenomenon more fully in Figure (4). The added ballots have a Biden percentage of around 70%, while the initial statitics were at 50%. This is a very large jump for such a large sample size and seems very unlikely. Indeed the probability that the fraud model is correct is 100%, up to the precision of double floating point arithmetic.

Assuming that the prior absentee ballot distribution is the correct one, we can form a simple prediction for how many of Biden's ballots were fraudulent. Let $N_1 = 303,988$, the number of ballots added, and let $B = 189,497$ be the number of Biden votes in this new batch. If the fraction of Biden votes should actually be $f = 0.509$. Let x be the proposed number of fraudulent Biden votes,

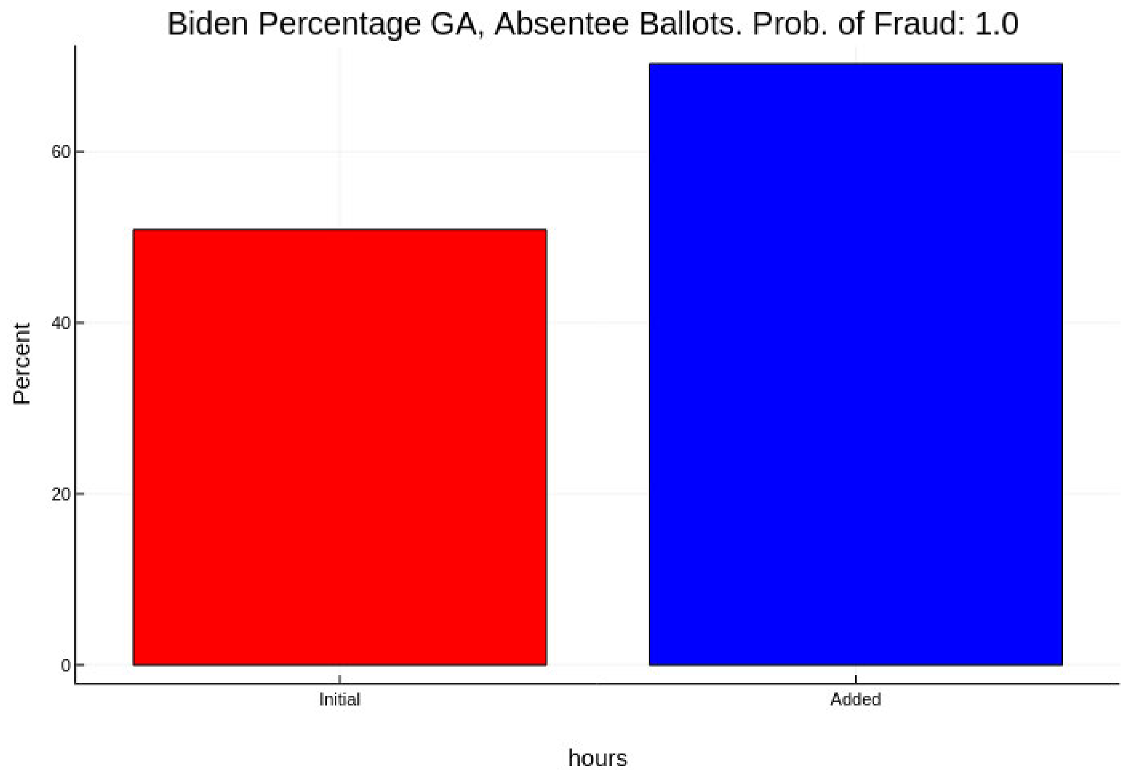

Figure 4: Before and After Biden Fraction in Georgia

then we have,

$$
\begin{aligned}
\frac{B-x}{N_1-x} &= f \\
x &= \frac{B-N_1 f}{1-f}. \qquad (4)
\end{aligned}
$$

In the case that votes were actually switched from Trump to Biden, then the formula becomes,

$$
\begin{aligned}
\frac{B-x}{N_1} &= f \\
x &= B-N_1 f
\end{aligned}
$$

This would suggest that 104,107 ballots were fraudulently manufactured for Biden. If we presume that actually those ballots were switched from Trump to Biden then as many as 19% of the new absentee ballots for Biden were fraudulent, which totals around 51,110 ballots that should be removed from Biden's totals and added to Trump. We shall see in Section 6, that there is substantial evidence that some Trump votes were actually switched to Biden votes.

3.3 Analysis of Pennsylvania Absentee Ballots

The Pennsylvania absentee ballot count started at 785,473 and 319,741 ballots were added at 39 hours after the start of the data record. The Biden fraction among absentee ballots as a function of time is shown in Figure (5). This plot shows some oddities in that the Biden fraction fluctuates with large deviations.

In Figure (6) we see the initial Biden percentage compared with the Biden percentage of the added ballots over the first 39 hours. The added ballots have a Biden percentage of around 83%, while the initial statistics were at 78%. This is a very large jump for such a large sample size and seems very unlikely. Indeed the probability that the fraud model is correct is 100%, up to the precision of double floating point arithmetic.

If we just examine the initial large batch of votes among the absentee ballots, we see an unexplained jump of 5% for Biden. Although it is likely that most of the fraud, if any, occurred earlier in the vote count, just this batch of ballots suggests that approximately 72668 Biden ballots are fraudulent. If we presume that the votes were stolen from Trumps votes, then 15987 Biden ballots are fraudulent and should be added to Trump's total.

4 Analysis of Milwaukee County in Wisconsin

We now switch our analysis to a data set that contains precinct data for Milwaukee county. The data was obtained from the twitter acount of @shylockh, who derived his sources from the New York Times and in some cases from

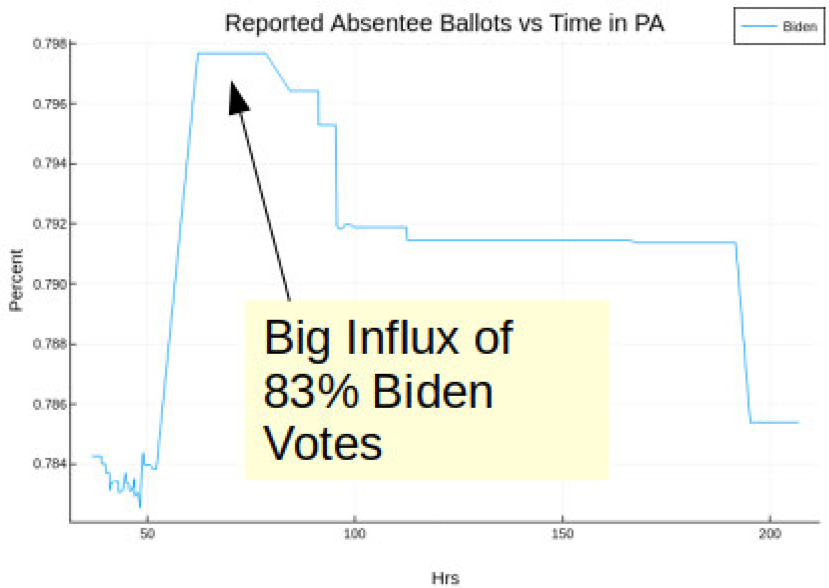

Figure 5: Pennsylvania Absentee Ballots vs Time: (Biden Fraction)

the unofficial precinct reports from the Wisconsin elections commision website. We examine vote percentages for ballots added between Wednesday morning, 11/04/2020 and Thursday night 11/05/2020.

This data set gives the total vote count by party affiliation. Because the data set is confined to Milwaukee, we can assume that the statistics should not be time varying. The voting pool here is highly partisan in favor of democrats and we don't expect any significant difference in the voting percentage, especially since a large number of absentee ballots were already counted by Wednesday morning.

4.1 Analysis of Milwaukee County Democrat results

The percentage of democrat voters increases by 15% among the ballots added on Wednesday and Thursday. On Wednesday morning Milwaukee had received 165,776 ballots. By Thursday evening 458,935 ballots were received, adding 293,159 ballots.

In Figure 7 we see the large deviation in democrat percentage between the Wednesday morning and those added by Thursday evening. This too causes the posterior probability of the fraud model to be 100% to machine precision.

Assuming that there was fraud, we estimate that 105,639 fraudulent Biden ballots were added between Wednesday and Thursday of 11/05/2020 in Milwaukee alone. However as we shall see below, many of these votes may well have been switched from Trump to Biden, which would also give Trump an additional

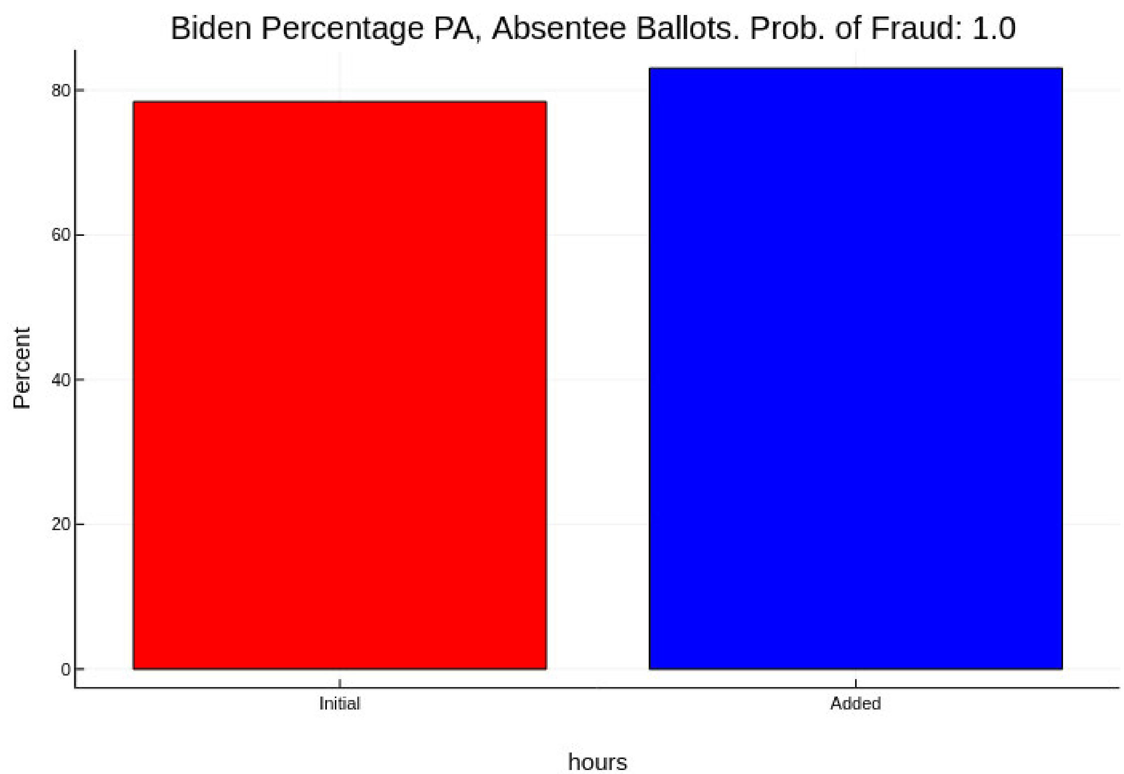

Figure 6: Before and After Biden Fraction in Pennsylvania

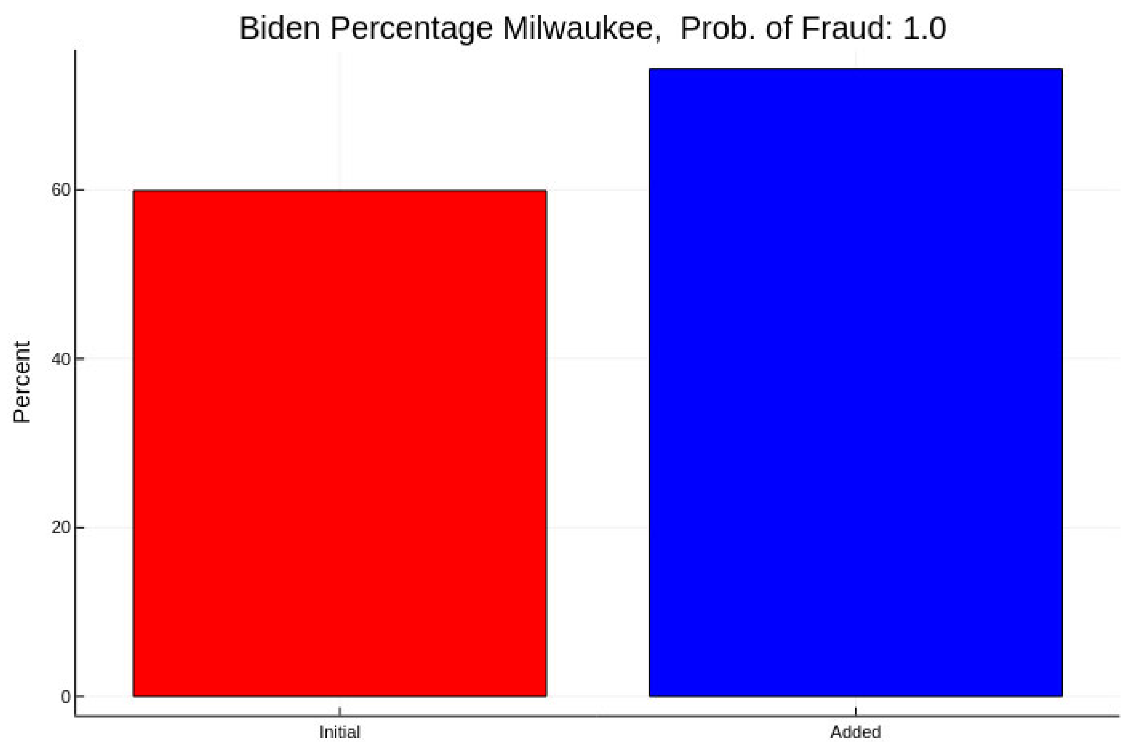

Figure 7: Before and After Democrat Fraction in Milwaukee

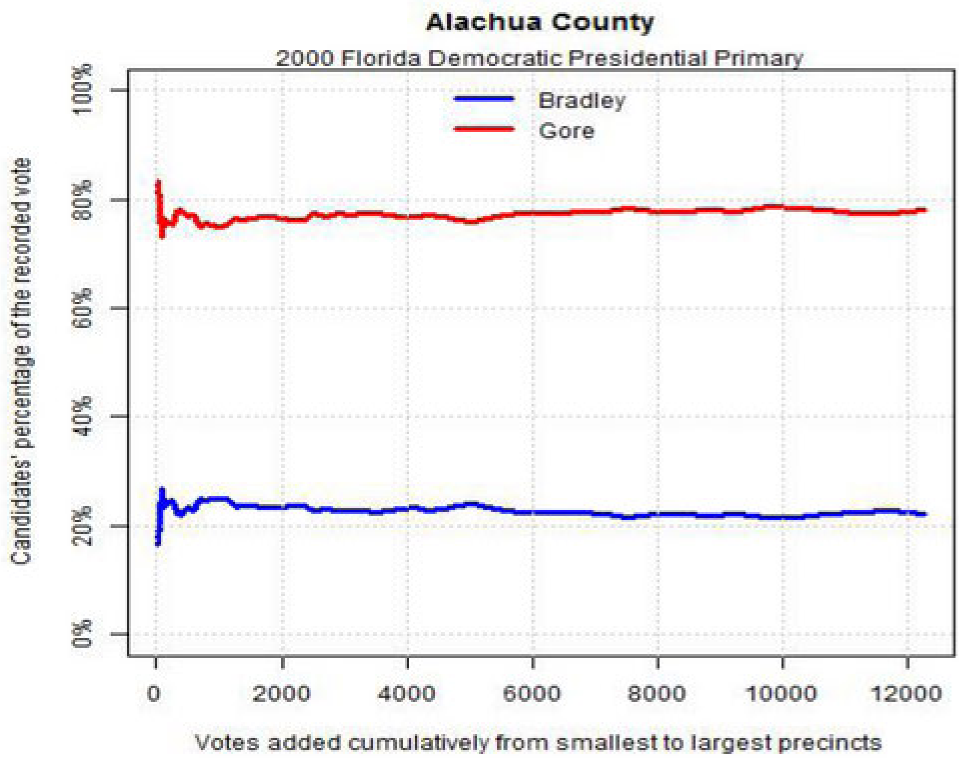

Figure 8: Baseline Cumulative Fractions Sorted by Precinct Size

42365 votes and remove 42365 votes from Biden.

4.2 Candidate Percentages Sorted by Ward Size

Another useful tool for evaluating fraud is to look at the cumulative vote percentages sorted by an independent input factor. An easy factor to use is ward or precinct size. This concept was used throughout the report on voter irregularities in [2]. In that report there was an anomalous dependency on precinct size in many of the 2016 primary elections. The larger precincts had introduced the use of voting machines. But one could also theorize the opportunity for cheaters to cheat in small precincts, where there may be less oversight.

Normally we would expect the cumulative vote percentage to converge to an asymptote, and bounce around the mean until convergence. An example of this can be found from the 2000 Florida Democratic presidential primary between Gore and Bradley. This is shown in Figure 8, and is taken from [2].

However when one sorts the Milwaukee, Thursday night data, by precinct

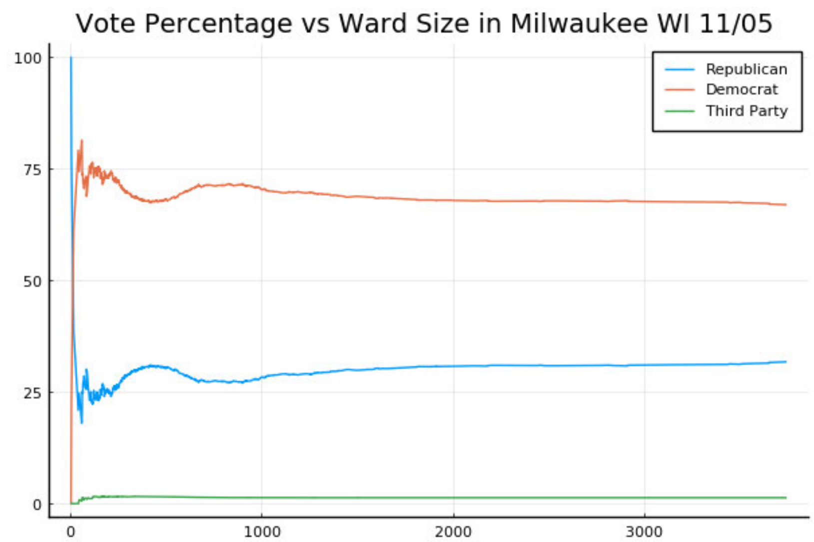

Figure 9: Milwaukee Democrat Ballots Percentage vs Ward Size

size, you will see trendlines that do not converge to an asymptote, as shown in Figure 9. It appears that smaller precincts almost uniformly have higher Democrat percentages. There is no obvious reason for this. It was certainly not seen in the control case in Figure 8. Furthermore the third party percentages quickly converge to their asymptote as would be expected in a fair election. One possible model for this would be vote switching from Trump to Biden, which would show up more strongly in the smaller precincts.

5 Analysis of Third Party Vote Count

Third party voters offer another way to examine a possible fraud mechanism. Votes could either be switched from third party candidates to the cheater, or fraudulent ballots that are added to benefit the cheater, may not include third party choices. For the control example, we look at absentee ballots in the state of Massachusetts. In Massachusetts the initial absentee ballot count was 117,618, and the number of added absentee ballots is 10,281.

The reported 3rd party percentage of absentee ballots vs time in Massachusetts is shown in Figure 10 and the comparison of the inital and added 3rd party ballots in MA is shown in Figure 11. There is only a small change in party preference, relative to the size of the added ballots. Therefore the probability of the fraud model is only 22%.

When we look at the total 3rd party percentages in Milwaukee, between Wednesday morning and Thursday night, we see a significant drop from 1.9 percent to 1.4% for the newly added ballots. But this is among 293,159 added

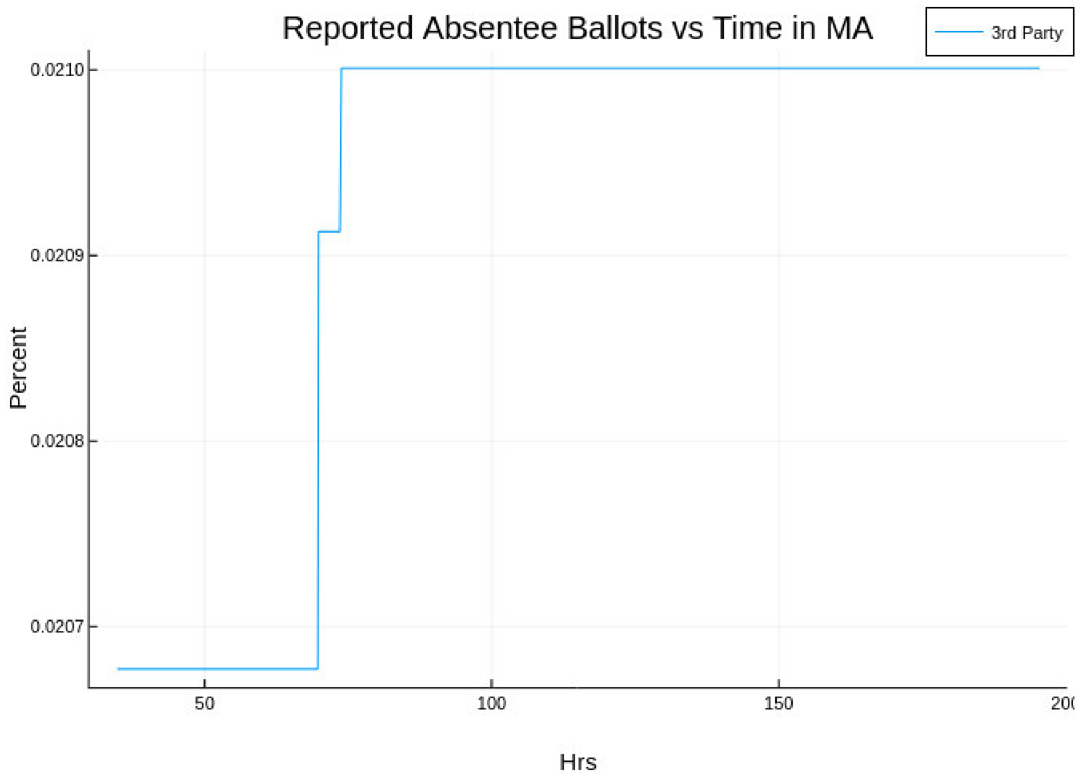

Figure 10: MA 3rd Party Absentee Votes vs Time

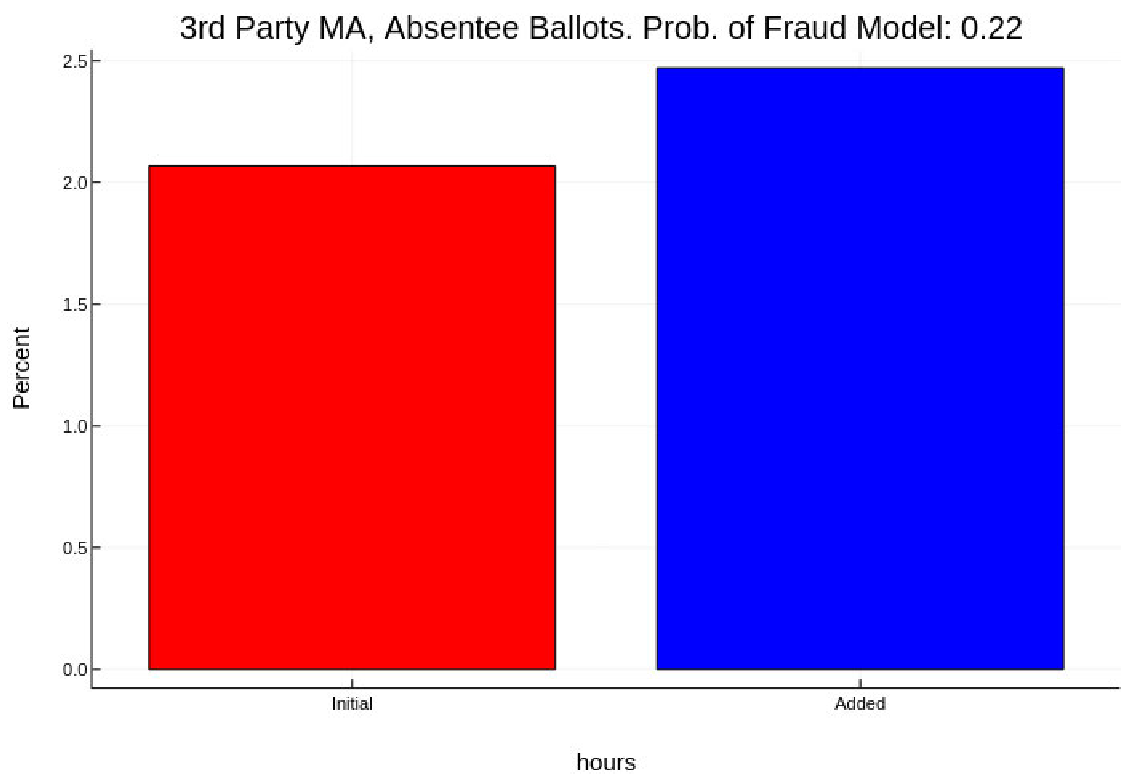

Figure 11: MA 3rd Party Percentage Initial and Added

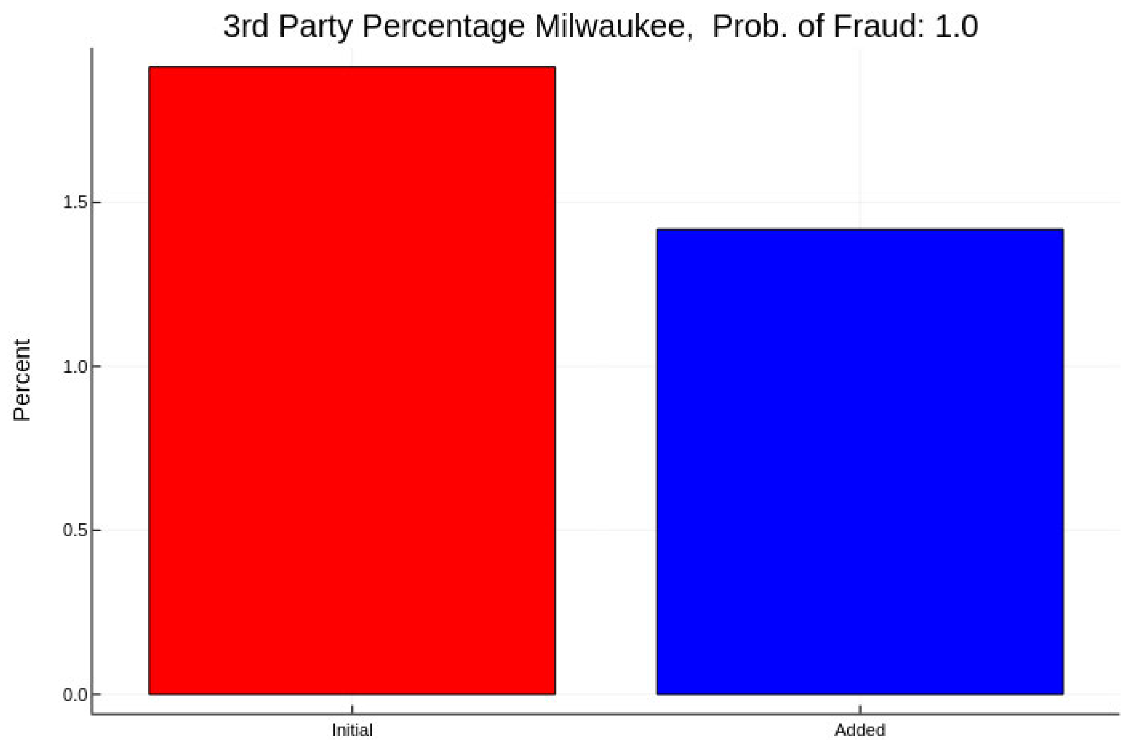

Figure 12: Milwaukee 3rd Party Percentages between Wednesday and Added

ballots. This is illustrated in Figure 12. Again in this case the fraud model has a posterior probability of 100% to machine precision.

6 Analysis of Fulton and DeKalb Counties in Georgia

We perform a precinct level analysis of Fulton and DeKalb counties in Georgia based on an aggregate data set likely culled from the New York Times. The Fulton data was collected on 11/08/2020 and the DeKalb data was collected on 11/09/2020. As in Milwaukee we look at the cumulative vote percentages as a function of precinct size. A plot of this for DeKalb county is shown in Figure 13.

Although there are somewhat concerning trendlines in the beginning, after the size 600 precinct mark, thereafter the overall picture is what one would expect of an election where the voter preferences are not dependent on precinct size. Both DeKalb and Fulton counties are in predominantly urban Atlanta,

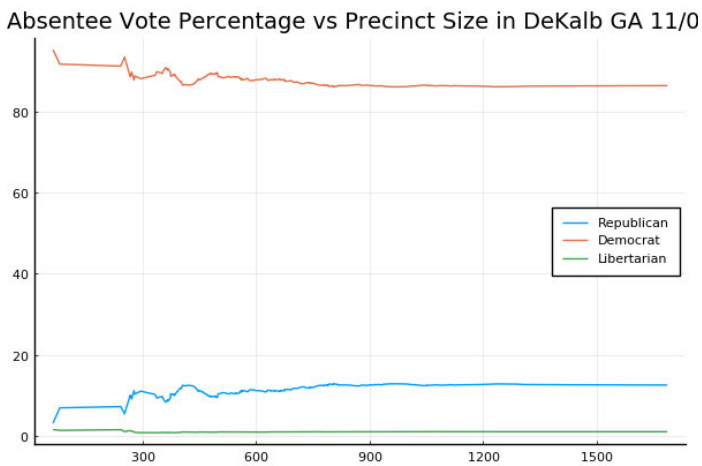

Figure 13: Dekalb County Absentee Ballots: Percentages vs Precinct Size

neighbor one another, and have similar voting preferences across precincts. DeKalb county is still suspect, however, due to the irregularites observed prior to the Ward 600 mark.

A different story emerges when we plot the absentee vote percentages for Fulton county as a function of precinct size, as can be seen in Figure 14. Here the trendlines for the Democrat and Republican percentages are quite pronounced, amounting to a difference of 8 percent from the halfway mark.

We divide the Fulton county data into a group of smaller precincts and larger precincts. One group has precincts less than 308 and another larger than 308. The total absentee ballots for the small group is 24,575, and the large group is 120,029. The small group has a Democrat percentage of 85% and the large group has a percentage of 77%, for a change of 8%. The fraud model is preferred in this scenario again with probability of 100% to machine precision.

One might presume that small precincts generally favor Democrats over large precincts, biasing the results. However take a closer look at the Libertarian party results in Fulton county in Figure 15. The percentages are exactly what we would expect if there were no bias in precinct size. The percentages bounce around a mean, not trending in any direction.

So if there were a bias favoring the democrats in small precincts, we would expect that to effect both the Republican and Libertarian totals. However it appears to only effect Republican totals, as if the Republican ballots were switched over to Democrat in a higher percentage in the smaller precincts. Indeed if a fixed number of ballots are switched in each district, it would have a larger effect in the smaller districts and then show up as trend lines in these percentage plots. At a minimum the data suggests a statistical anomaly that is not normally present in a fair election.

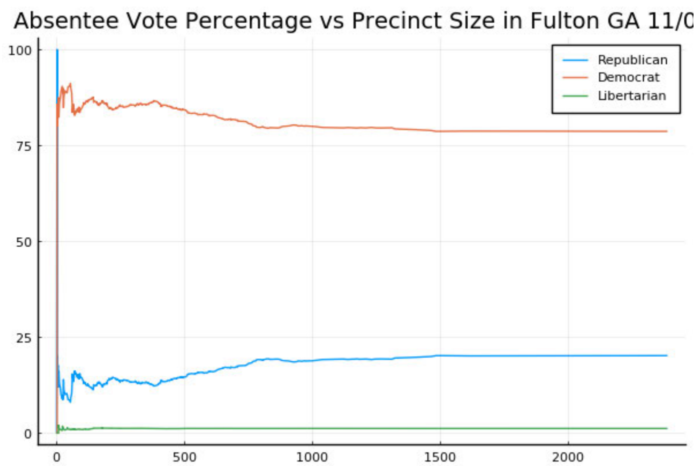

Figure 14: Fulton County Absentee Ballots: Percentages vs Precinct Size

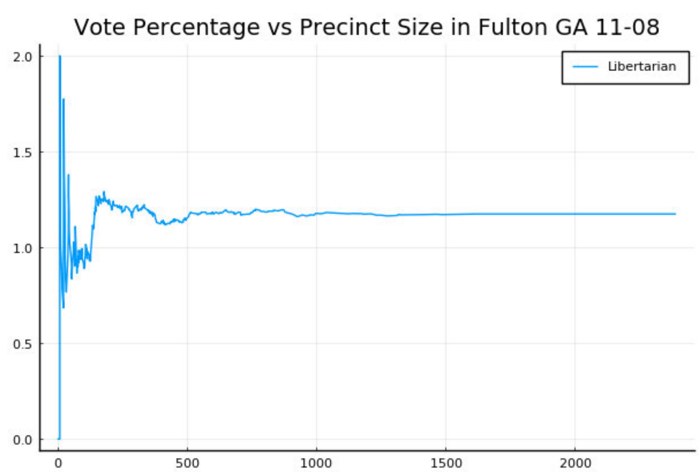

Figure 15: Fulton County Absentee Ballots: Libertarian Percentage vs Precinct Size

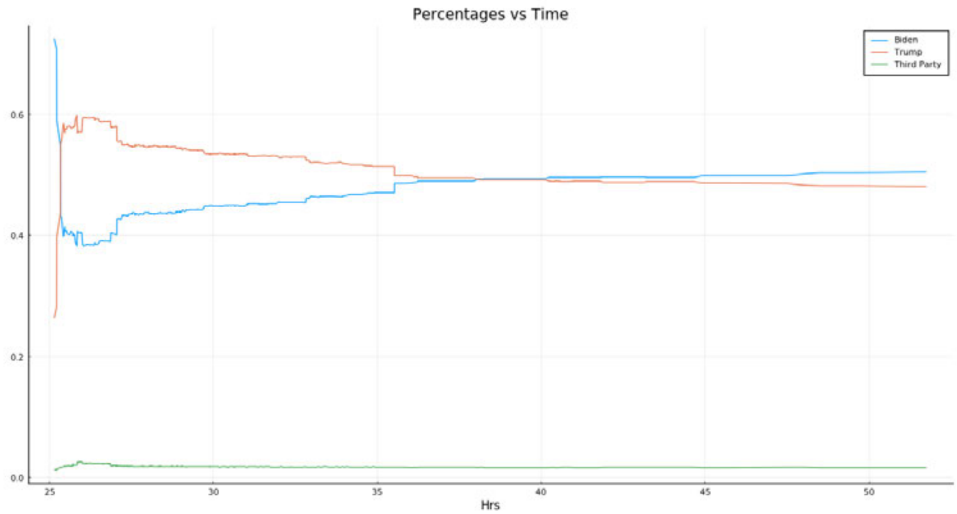

Figure 16: Michigan Vote Percentage vs Time

7 Michigan Analysis

We now due a time series analysis for Michigan. The data was culled from Edison Research. We first show, Trump, Biden and 3rd party voting percentages vs hours after the start of the election in Figure 16. The third party votes shows the proper convergence to an asymptote that we would expect from the law of large numbers. However the Trump and Biden percentages are vastly different You can see large discrete jumps in the percentages as very large Biden ballot dumps occur over time. You also see that the Biden percentages are mostly always increasing after hour 27, which is statistically unlikely in a fair election.

Note also that almost a million of the ballots are received by hour 27, and we use this as our starting point. At that point we have a total of 970,119 votes cast. At the end of 167 hours we have 5,531,222 votes cast. At our initial point the Biden percentage is 38%, but the new ballots have a Biden percentage totaling 53% as seen in Figure 17. The fraud model has posterior likelihood of 100% to machine precision.

For Michigan we compute the estimated amount of fraudulent Biden ballots conservatively, assuming that the 50.5 percent seen at the end of the count should have been the correct percentage among the newly added ballots. From this and (4) we obtain an estimate of 237,140 fraudulent votes added for Biden.

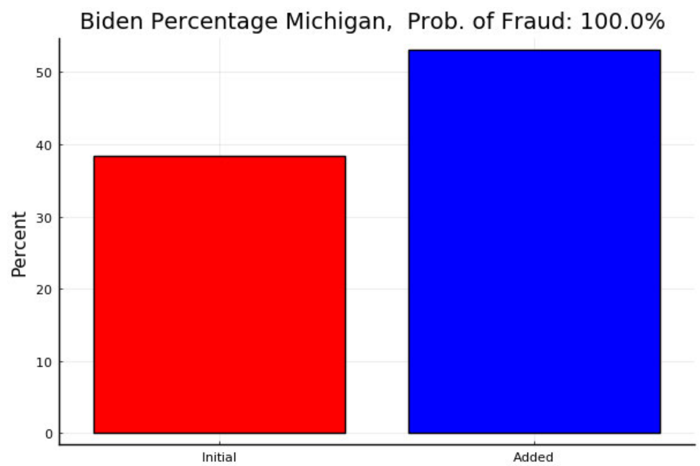

Figure 17: Biden Percentage Before and Added

References

[1] Peter Klimek, Yuri Yegorov, Rudolf Hanel, and Stefan Thurner. Statistical detection of systematic election irregularities. 2, 2.1

[2] lulu Fries'dat and Anselmo Sampietro. An electoral system in crisis. http://www.electoralsystemincrisis.org/. 4.2